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Original Research

With a little help...: On the role of guidance in the acquisition and utilisation of knowledge in the control of complex, dynamic systems

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Many situations require people to acquire knowledge about, and learn how to control, complex dynamic systems of inter-connected variables. Numerous studies have found that most problem solvers are unable to acquire complete knowledge of the underlying structure of a system through an unguided exploration of the system variables; additional instruction or guidance is required. This paper examines whether providing structural information following an unguided exploration also improves control performance, and the extent to which any improvements are moderated by problem solvers' fluid intelligence as measured via Raven's APM. A sample of 98 participants attempted to discover the underlying structure of a computer-simulated complex dynamic system. After initially controlling the system with their independently acquired knowledge, half of the sample received information and an explanation of the underlying structure of the system. All participants then controlled the system again. In contrast to the results of previous studies, the provided information resulted in immediate improvements in control performance. Fluid intelligence as measured via APM moderated the extent to which participants benefited from the intervention. These results indicate that guidance in the form of structural information is critical in facilitating knowledge acquisition and subsequent use or application of such knowledge when controlling complex and dynamic systems.

Keywords: complex problem solving, dynamic systems, knowledge acquisition, fluid intelligence, discovery learning

Many situations require us to acquire knowledge about, and learn to control, dynamic systems of causally connected variables. Learning how to heat food in a microwave, respond to emails and buy train tickets are just a few of the many examples that might be encountered in everyday life. A significant body of research has examined the conditions that facilitate the acquisition of knowledge about complex and dynamic systems (de Jong & van Joolingen, 1998; de Jong, Linn, & Zacharia, 2013). A question that has been addressed less frequently is how is knowledge best acquired to most effectively control such systems? This paper examines whether structural information (i.e., an explanation of how each input affects each output with a diagram that depicts the system variables, the direction and strengths of their interrelation) confers any advantage over an unguided exploration of the system, its variables and their interconnectedness. We also investigate the role of fluid intelligence as measured via Raven's Advanced Progressive Matrices (APM; Raven, Raven, & Court, 1998) in utilising this information.

The complex problem solving (CPS) approach

To investigate how people learn how to control complex and dynamic systems in the real world, a wide variety of computer-based problem-solving scenarios have been developed (e.g. Berry & Broadbent, 1984; Dörner, 1980; Funke, 1992; for a review see Osman, 2010). The study presented in this article was underpinned by the DYNAMIS or complex problem solving (CPS) approach, introduced by Funke (1992; 2001; see Blech & Funke, 2005 for a review). CPS tasks consist of a number of inputs (variables that the problem solver intervenes on) and outputs (outcomes that are generated by the system) that are governed by a set of linear equations (this is referred to as the underlying structure of the system). The systems are dynamic in the sense that the current output value depends on the value of the input selected by the problem solver, and the previous value of the output. Some CPS tasks also include autonomic changes, so that the values of particular output variables change independently on each trial. A typical experimental procedure using this approach consists of an initial *exploration phase* in which problem solvers are required to diagnose the underlying structure of the system. In a subsequent *control phase* they are instructed to control the system by manipulating the input variables to reach and maintain specific goal values of the output variables. This means that separate measures of structural knowledge and control performance can be derived, and the cognitive processes of knowledge acquisition and knowledge application can be studied independently.

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The role of structural knowledge in controlling a complex, dynamic system

The acquisition of knowledge through an unguided exploration of a system and its interrelated variables can be characterised as discovery (De Jong & van Joolingen, 1997; 1998) or inquiry-based learning (Lazonder & Harmsen, 2016). In this approach, the learner is seen as an independent and active agent in the process of knowledge acquisition, as they must develop hypotheses, design experiments to test them, and appropriately interpret the data (De Jong & van Joolingen, 1998).

In educational settings, the problems that learners experience with unguided inquiry-based learning are well documented. A recent meta-analysis of 164 studies found that across domains, unguided inquiry-based learning is less effective than explicit instruction for acquiring knowledge. However, the advantage is reversed when learners receive adequate guidance during inquiry-based learning; they learn more than those taught using explicit instruction (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011). Numerous studies in educational settings have also found that learners need at least some guidance during exploration in order to facilitate the acquisition of complete structural knowledge (De Jong & van Joolingen, 1998; De Jong, 2005, 2006; Kirschner, Sweller & Clark, 2006; Lazonder & Harmsen, 2016; Mayer, 2004).

Similarly, in research with CPS tasks, it has been found that most problem solvers are unable to acquire a complete or accurate representation of the underlying structure of the system through an unguided exploration of the system variables (Beckmann, 1994; Beckman & Guthke, 1995; Burns & Vollmeyer, 2002; Funke & Müller, 1988; Kluge, 2008; Kröner, 2001; Kröner, Plass & Leutner, 2005; Müller, 1993; Osman, 2008; Schoppek, 2002; Vollmeyer, Burns, & Holyoak, 1996). These studies also report a consistent positive relationship between the amount of structural knowledge that is acquired and the quality of problem solvers' control performance (see *Knowledge Hypothesis*).

It is worth noting that the majority of these studies are correlational and therefore do not allow for causal interpretations of the reported association between knowledge and control performance. The study of Goode and Beckmann (2010) is one of the rather rare examples where an experimental design was adopted to test the causal nature of this association. They found that control performance improved systematically as the amount of structural information available to participants increased, and that at least some structural knowledge was required to perform better than simulated random control interventions. This study illustrates that control performance is causally dependent on the amount of knowledge that is acquired about the underlying structure of the system.

The impact of providing structural information on control performance

In this study we are interested in determining whether supplementing problem solvers exploration of a CPS task with structural information results in better control performance than an unguided exploration of the system variables.

A study conducted by Süß (1996, p. 166-177) suggested that providing structural information benefits structural knowledge, but confers no advantage for control performance. This study used a dynamic decision-making task called "TAILORSHOP", which is intended to simulate a small business that produces and sells shirts. The system consists of 24 variables inter-connected by 38 relations. The values of twenty-one of these variables are represented on the user-interface, and three are invisible. Twelve of the variables can be manipulated directly by participants, and the goal is to increase the value of the variable "company value" (Danner et al., 2011). The underlying structure is intended to reflect problem solvers' prior knowledge of similar "real world" scenarios (see Beckmann & Goode, 2014 for a discussion of the problems associated with this assumption).

In Süß's (1996) study, one group of participants explored "TAILORSHOP" while another group studied a causal diagram for the same time period, before both performing the control task. A control group performed the control task without any prior exploration or intervention. Structural knowledge was assessed prior to, and after, interacting with the task. The group that studied the causal diagram acquired more structural knowledge than the exploration group; there was no difference between the exploration and control group. Surprisingly, there was no differences in control performance across the conditions. Thus, the causal diagram appeared to benefit structural knowledge but not control performance. However, these results should be interpreted with caution, as a strong associative link was found between structural knowledge prior to interacting with the task and control performance across all conditions. On the one hand, this could be interpreted as an indicator of the "ecological validity" of the system. On the other hand, the already substantial correlation between prior knowledge and control performance limits the potential impact of the interventions (i.e. knowledge acquisition through causal diagram or exploration), and introduces a potential source of individual differences among participants.

A number of studies using abstract systems (Putz-Osterloh, 1993; Preußler, 1996, 1998) also report similar results to Süß (1996). These studies suggest that problem solvers require a period of active practice applying structural information before they demonstrate an advantage over knowledge acquired through unguided exploration (Putz-Osterloh, 1993; Preußler, 1996; Preußler, 1998). These studies used the CPS task "LINAS", which contains four inputs and seven outputs interconnected by fifteen linear relations. The labels given to the system variables did not refer to objects in the real world (e.g. "Bulmin", "Ordal", "Trimol") to control for the influence of prior knowledge. In Putz-Osterloh's (1993) study an experimental group (given a causal diagram) and a control group were first instructed to diagnose the underlying structure of a system by exploring the system variables. The causal diagram illustrated the input and output variables as rectangles linked by arrows to indicate the relationships between them; the meaning of the diagram was verbally explained by the experimenter. Against expectations, the experimental group performed no better than the control group in a subsequent control task. However, in a follow-up study six months later, the experimental group had better control performance than the control group. Given that the advantage to performance was only evident after participants had considerable exposure to the task, Putz-Osterloh (1993) suggested that problem solvers might need a period of practice applying their knowledge in order to benefit from structural information. However, caution is urged in interpreting these findings due to the relatively small sample size (N = 16 - 25 per condition).

Putz-Osterloh's (1993) interpretation of her findings found further support in a series of studies conducted by Preußler (Preußler, 1996, 1998). In the first experiment, participants in an experimental group were instructed using standardised examples as to how each input affected each output; a control group explored the system without assistance. No differences in control performance were found. In line with Putz-Osterloh's (1993) study, it was argued that the structural information did not provide an advantage to control performance because participants did not have a chance to practice applying it (Preußler, 1996). Therefore, in a later experiment, Preußler (1998) gave an experimental group a causal diagram, and in addition they completed practice tasks in which goal values had to be attained by manipulating the input variables. Each task was repeated until the problem solver reached the target values. The control group had to perform the same practice tasks, although without having the diagram available and without having the chance of retries until the correct response was found. This time the experimental group had better control performance (Preußler, 1998). These findings have been interpreted as demonstrating that structural knowledge needs to be either actively acquired or practiced in the context of application in order to benefit control performance (Preußler, 1996, 1998; Schoppek, 2004), a notion that resonates with the broader literature on "learning by doing" and cognitive skill acquisition (e.g. Anderson, 1993).

An alternative explanation is that the "guidance" given to participants in these studies was not sufficient to immediately promote structural knowledge (Goode & Beckmann, 2010). Specifically, Goode and Beckmann (2010) argue that in Putz-Osterloh's (1993) study participants may not have understood how the diagram related to changing the input and output variables. In order to understand the meaning of the diagram, problem solvers may require a direct demonstration of how the inputs affect the output. Whilst problem solvers in Preußler's, (1996) study did receive an explanation as to how the inputs affect the outputs, they did not receive a structural diagram. It is likely that they may have been unable to recall this information during the control task. Goode and Beckmann (2010) developed instructional material to overcome these limitations, and compared control performance under conditions of complete, partial or no structural information. They used a CPS task with three inputs and three outputs, interconnected by six linear relations. As in Putz-Osterloh's (1993) and Preußler's (1996, 1998) studies, the labels given to the system variables did not refer to objects in the real world (e.g. "A", "B", "C"). The instructional material included an audio-visual demonstration of how the inputs affect the outputs, and the formation of a causal diagram as a result of the interventions shown. This information was then available on screen during the subsequent control phase. They found that problem solvers who received complete information were significantly better at controlling the system than those who received partial or no information. This study illustrates that structural information can have an immediate positive impact on the quality of control performance, without a period of goal-orientated practice or prior exposure to the system. The findings suggest that the effectiveness of providing structural information is more a matter of accessibility (i.e., instructional design), rather than practice.

Another factor that appears to influence the application of structural information is the complexity of the underlying structure of the CPS task. In a follow-up study to Goode and Beckmann (2010) using the same methodology, Goode (2011) provided participants with either complete, partial or no structural information regarding the underlying structure of one of four CPS tasks, which varied in system complexity. The complexity of the tasks was manipulated by increasing the number of relations that had to be processed in parallel in order to make a decision about a particular goal state (i.e., the connectivity of the goal state). The study showed that it was more difficult for subjects to understand and utilise information as system complexity increased; floor effects on performance were observed when three relations had to be considered in parallel to make a decision about a goal state. This may also explain why previous studies have found that structural information did not benefit control performance (Putz-Osterloh, 1993; Preußler, 1996, as "LINAS" is at this level of complexity. Süß's (1996) study employed a task with many more variables and relations. This may have made it more difficult for subjects to understand and utilise the information that they were given.

Nevertheless, the issue of whether the provision of structural information results in immediate improvements for control performance after knowledge has already been acquired through an unguided exploration remains unresolved. Goode and Beckmann's (2010) and Goode's (2011) studies did not include a comparison with a group who acquired knowledge through an unguided exploration of the system variables.

The aim of the current study is to determine whether structural information can directly benefit control performance. To allow direct comparisons to control performance scores from Goode and Beckmann (2010), this study will use the same CPS task, intervention and performance goals. In our proposed design, participants will first explore a CPS task, and try to independently acquire knowledge about its underlying structure. They will then try to control the system to reach specific goal values of the output variables. Participants in an experimental condition will then watch an audio-visual demonstration of how the inputs affect the outputs, and will observe the formation of a causal diagram as a result of the interventions shown (as per the procedure reported in Goode and Beckmann, 2010 and Goode, 2011). Both the experimental and the control group will then control the system again. If structural information can be immediately utilised, then problem solvers who receive structural information should show an improvement in their control performance, and should be better controlling the system than those who have to rely on the knowledge they acquired independently (see *Information Hypothesis*).

The role of fluid intelligence in benefiting from structural information

A second issue addressed by this study is whether benefiting from structural information is dependent on the cognitive abilities of the problem solver. Goldman (2009) has argued that learner characteristics, such as prior knowledge and cognitive ability, determine whether benefits are derived from instructional settings. The CPS task employed in the current study uses abstract variable labels and a domain-neutral cover story. This aims at minimising confounding effects of individual differences in domain-specific knowledge on the results (for a detailed discussion of the argument for using abstract systems in complex problem solving research see Beckmann & Goode, 2014). Consequently, the guidance information provided (i.e., the intervention) is expected to be relatively novel for all participants, so that individual differences in utilising it can largely be attributed to the cognitive abilities of the problem solver.

Previous findings show that when explicit information about system structure is provided, control performance is consistently moderately to strongly correlated with fluid intelligence (Bühner, Kröner, & Ziegler, 2008; Goode & Beckmann, 2010; Kröner et al., 2005; Putz-Osterloh, 1981; Putz-Osterloh & Lüer, 1981; Wüstenberg et al., 2012). Therefore, in the current study it is predicted that under conditions where participants receive information, the extent of improvements in control performance will be a function of their fluid intelligence as measured via APM. In comparison, the extent of improvements in control performance when participants do not receive additional information should be due to practice applying their partial representations of the underlying structure, and therefore less strongly related to fluid intelligence as measured via APM (see *Intelligence Hypothesis*).

Aims and hypotheses

In summary, the main goal of this paper is to determine whether guidance in the form of structural information results in an immediate improvement in controlling a CPS task after knowledge has already been acquired through an unguided exploration of the system variables. A secondary aim is to examine whether any improvements are moderated by fluid intelligence as measured via APM. Firstly, it is hypothesised that participants who acquire more knowledge during the exploration phase about the underlying structure of the system should show better control performance prior to any instructional intervention (*Knowledge Hypothesis*). Secondly, participants who receive structural information should improve their control performance more than those who receive no additional information (*Information Hypothesis*). Thirdly, under conditions where participants receive information, the magnitude of this improvement will be a function of their fluid intelligence as measured via APM (see *Intelligence Hypothesis*).

Method

Participants

Ninety-eight first year psychology students at the University of Sydney, Australia, participated for course credit. Nine participants failed to complete all tasks therefore their data were excluded from further analysis. The available sample size of about 100 would guarantee sufficient statistical power ($1 - \beta \geq .80$) in identifying at least medium effects ($d = 0.50$) at a significance level of $\alpha \leq .05$ (one-tailed) in the planned analyses.

Design

Participants were randomly assigned to one of two conditions (45 participants in the *Information* condition, 44 participants in *No Information* condition). As problem solvers were required to control the system on two occasions this resulted in a 2 x 2 design. The within-subjects factor was control performance (cycle 1 and cycle 2). The between-subjects factor was whether or not they received structural information (Information and No Information). The aim of the intervention in the information condition was to encourage participants to develop a complete and accurate representation of the underlying structure of the system. The no information condition represented a passive control group. Participants were assessed on their structural knowledge, control performance for cycle 1, control performance for cycle 2 and performance in a test of fluid intelligence. Vary-one-thing-at-time (VOTAT) strategy use during the exploration phase was also assessed as part of this study; this measure is not reported in this paper. Figure 1 displays the procedure of the experiment for each condition and indicates which performance measures were collected in each phase of the experiment.

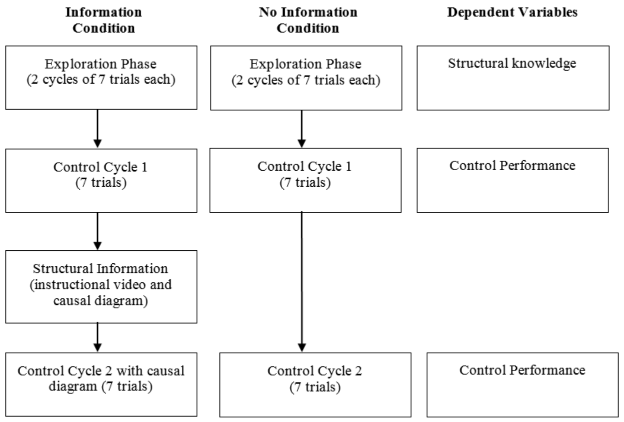

Figure 1. Diagram for the procedure of the experiment, illustrating the phases of the experiment by condition and indicating which performance measures were collected in each phase.

Description of CPS task

The CPS task was programmed using Adobe Flash 8 and Captivate 3, and administered on PCs (see (Goode, 2011 for an extensive description of all of the CPS task elements, including step-by-step screenshots of the instructional intervention and CPS task, and transcript of the explanation).

The underlying structure was originally developed by Beckmann (1994, see also Beckmann & Goode, 2014; Goode & Beckmann, 2010; Goode, 2011), and is based on the approach to complex problem solving that was developed by Funke (1992) in his DYNAMIS research project. It consists of three input and three output variables that are connected by a set of linear equations:

$$X_{t+1} := 1.0 * X_t + 0.8 * A_t + 0.8 * B_t + 0.0 * C_t$$
$$Y_{t+1} := 0.8 * Y_t + 1.6 * A_t + 0.0 * B_t + 0.0 * C_t$$
$$Z_{t+1} := 1.2 * Z_t + 0.0 * A_t + 0.0 * B_t + a.0 * C_t$$

X_t, Y_t and Z_t denote the values of the output variables and A_t, B_t and $C_t$denote the values of the input variables during the present trial whilst X_{t+1}, Y_{t+1} and Z_{t+1} denote the values of the output variables in the subsequent trial.

Important for the operationalization of knowledge acquisition, the system can be considered balanced, i.e., from 12 possible relationships between variables 6 do exist and among the three output variables one is subject to a "positive" eigendynamic (i.e., an autoregressive dependency that results in a monotone increase), one is subject to a negative eigendynamic (i.e., an autoregressive dependency that results in a monotonic decrease) and one is subjected to no eigendynamic and all three output variables have a double dependency.

Previous research has found that the presence of a semantically meaningful context has an unpredictable, often negative, effect on acquisition of structural knowledge (Beckmann, 1994, see also Beckmann & Goode, 2014; Burns & Vollmeyer, 2002; Lazonder, Wilhelm, & Hagemans, 2008; Lazonder, Wilhelm & van Lieburg, 2009.) Therefore, in order to ensure that the system was relatively novel for all participants and thus control the potential influence of prior knowledge, the input and output variables are labelled with letters. As can be seen in Figure 2, the output variables are labelled X, Y and Z, whilst the input variables are labelled A, B, and C.

The user-interface is in a non-numerical graphical format, in order to encourage the formation of mental representations more aligned with the development of causal diagrams. In accordance with the principles of cognitive load theory (CLT), this should minimise the cognitive activities that are not directly relevant to the task (extraneous cognitive load, e.g. Sweller, 1994; for a review see Beckmann, 2010; Sweller, 2010). Figure 2 shows that the values of the input variables are represented as bars of varying heights in the boxes on the input variables, where positive values are shown above the input line and negative values are shown below. Each box represents the value of the input variable on a single trial, and in total seven trials can be conducted before the values are reset (representing a single cycle). Although the numerical values of the inputs are not available to participants, the inputs are varied in increments of one unit, within the range of -10 to 10.

On each trial, participants have to set value of each input variable. This is done step by step, such that after they set the value for input A, they then have to set the value for input B and finally input C before the resulting values of the output variables are displayed as line graphs below. Previous inputs and there subsequent effects remained on the screen (decision history) for each cycle of seven trials. There was no time limit.

During the control phase of the task, the goals are indicated as dotted lines on the graphs for the output variables (as show in Figure 2). The target values used for control cycle 1 and 2 were of comparable in difficulty, i.e., the Euclidean Distance (see operationalization of control performance) between start values and target values was the same for both cycles.

Dependent variables and individual differences measure

Structural knowledge

Participants' structural knowledge was assessed by asking them to create causal diagrams of the relationships between the input and output variables at the end of each trial during the exploration phase. The

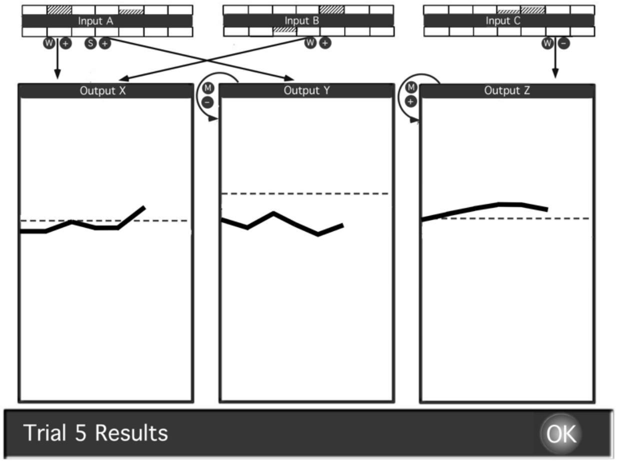

Figure 2. Screenshot of the system interface, as presented in the information condition after the instructional phase. The goals are indicated as dotted lines on the graphs for the output variables. The underlying structure of the system is represented on screen as a causal diagram, where the arrows represent the relationships between the variables, while the positive and negative signs denote the direction of the relationship, and the letters the relative strength. In this example, for the fifth trial of seven all input variables were increased (A half the strength and B and C using the maximum); as a result, Output X and Y increased whilst Output Y decreased slightly.

diagram that was generated on the final exploration trial (after 2 cycles of 7 trials), before the control phase was used to derive a structural knowledge score. Using a procedure introduced by Beckmann (1994), the operationalisation of the knowledge acquisition performance is based on a threshold model for signal detection (Snodgrass & Corwin, 1988). The proportion of correctly identified relationships was adjusted for guessing by subtracting the proportion of incorrectly identified relationships. The final score has a theoretical range from -.98 to .98, where a score below zero indicates inaccurate knowledge, whilst a score above zero indicates more accurate knowledge.

Control performance

The scoring procedure used was based on Beckmann's (1994) scoring system. Control performance was calculated by determining the Euclidean Distance between the vectors of actual and optimal values of the input variables. The ideal values for each input variable, i.e., the intervention that would result in the system reaching the goal state, were calculated by using the values of the output variables on the previous trial and the goal output values to solve the set of linear equations underlying the system. As the range of possible input values is restricted for the system used in this study (i.e., between -10 and 10), it might not be possible to bring the system into the goal state by a single intervention. In cases as these, i.e., when the ideal values fall outside this range, the values were adjusted to the nearest possible values, which then constituted the optimal values. In cases when the ideal values are within the range of possible inputs, the ideal values were used as the optimal input.

For the system at hand the theoretical range of this score is 0 to 34, where a lower score indicated a smaller deviation from optimal control interventions and therefore better performance.

Fluid intelligence

The percentage of correct responses on an abridged version of the Raven's APM (Raven et al., 1998) was used as an indicator of fluid intelligence. This version of the APM included 20 items from the original 36-item test, created using the odd numbered items plus 2 additional even numbered ones from the most complex items (i.e. items 34 and 36).

Procedure

The CPS task and the APM were presented to participants on PCs, over two separate sessions. The CPS task for each condition was installed on alternate computers at the study venue. On arrival at the first session, participants chose a computer, which determined their condition.

The CPS task began with a set of instructions that explained the user-interface, how to change the values of the input variables and how to record and alter the causal diagram. At the end of the instructions, participants were informed that the task consists of two phases. Firstly, they had to explore the system to discover the underlying structure of the system and then control the system to reach certain values of the output variables. The goal values were not revealed until the beginning of each control cycle.

The exploration phase then began, in which participants were prompted to explore the system for two cycles of 7 trials each by changing any of the input variables and observing the effect on the output variables displayed in the graphs. At the end of each trial, participants had to record what they had learned about the system using the causal diagram construction feature that was displayed on the screen.

The causal diagram could be altered using a set of twelve buttons (one for each possible relationship in the system) at the bottom of the screen. Each button referred to a particular relationship in the system. Using these buttons, participants could record if they thought there was a relationship between two variables or not, or if they thought the output variables changed independently (or not). They could also specify the direction of the effect, and its perceived strength.

After the exploration phase, participants then had to control the system by manipulating the inputs to reach set values of the outputs for seven trials, which were indicated as dotted lines on the output graphs (Control Cycle 1). The causal diagrams they had constructed during the exploration phase remained on screen, providing access to the structural information they had individually extracted.

In the information condition, participants then watched an instructional video that explained the actual underlying structure of the system. The instructions were designed in accordance with the principles of CLT, and the aim was to reduce the amount of cognitive activities that problem solvers would have to undertake to translate the information provided into knowledge about the system (minimising extraneous cognitive load). In particular, previous research has shown that learning is facilitated when explanations of graphical information is presented aurally, rather than as text (modality effect, Tabbers, Martens, & van Merriënboer, 2004). Therefore, the instructions consisted of a recording of seven intervention trials with an accompanying audio narration, which explained the actual underlying structure of the system. After each trial, the narrator explained how each of the outputs had changed, and how this reflected the underlying structure of the system. The respective causal diagram was constructed on screen in parallel, to record this information. Participants in the no information condition did not receive any additional information during this phase; representing a passive control group.

All participants then had to control the system again for seven trials, with different goals indicated on the output variables (Control Cycle 2). In the information condition the causal diagram displayed onscreen was the correct and complete one. In the no information condition, the causal diagram that participants had constructed in the initial exploration cycles was displayed onscreen.

In a subsequent session, approximately one week later, participants completed the APM.

Data Analysis

To test our main hypotheses we conducted a series of hierarchical linear modelling analyses using the HLM software package (Raudenbush, Bryk, Cheong, & Congdon, 2000). This approach allows us to model individuals' change in performance from control cycle 1 to control cycle 2 as function of person-level variables (see Raudenbush & Bryk, 2002)). We used a two level model in which performance in control cycle 1 and control cycle 2 (level 1) were clustered within individuals (level 2). The specific analyses that we performed to test each hypothesis are discussed in the results section.

Results

The following sections first present preliminary analyses undertaken to test whether the random assignment to condition was effective, and justify our treatment of the variables in the following analyses. The findings in relation to the three hypotheses are then presented.

Intercorrelations (Pearson) between the variables used in this study as well as descriptive statistics and distributions are presented in Table 1. The distributions of the variables indicate that assumptions of normality were met.

Equivalence between the conditions prior to the intervention

To examine the effect of the intervention and fluid intelligence on control performance, firstly, it was necessary to check whether the conditions differed prior to the intervention. The amount of structural knowledge acquired by participants during the exploration phase did not differ by condition; $t(87)$ = -.09, p = .93, $d = 0.02$, nor did their control performance scores in cycle 1; $t(87)$ = -.05, p = .96, $d = 0.01$, or scores on the APM; $t(87) = 1.59$, p = .12, $d = 0.34$. This suggests that the procedure used to randomly allocate participants to the conditions was effective.

Structural knowledge acquired during the exploration phase

For both conditions, the amount of structural knowledge that was acquired during the exploration phase was significantly greater than zero; M = .22, SD = .34, $t(88) = 6.00$, $p <$ .01. This indicates that on average, participants had acquired some knowledge of the underlying structure of the system prior to the first control cycle. However, the range of structural knowledge scores, -.49 to .98, indicates that participants differed widely in the amount of knowledge that they were able to acquire about the underlying structure of the system during the initial exploration phase. That is, while some participants were able to acquire complete knowledge of the underlying structure of the system (one participant in the no information condition, and two participants in the information condition), others acquired a rather incorrect representation of the underlying structure. This also suggests that for the majority of problem solvers the provision of structural information could potentially represent a significant source of new information about the underlying structure of the system.

Internal consistencies

Internal consistency analyses were conducted to determine the variability in control performance scores across the trials and for different goal states as an estimate of the reliability of the dependent variables. Internal consistency was good across the first control cycle (ω = .85, 95% CI [.79, .89]) and the second control cycle (ω =.93, 95% CI [.89, .95]) (Dunn, Baguley, & Brunsden, 2014). This indicates that problem solvers are rather consistent in their performance and it justifies averaging the scores across each control cycle.

A further analysis indicated that the reliability of the APM scores was acceptable across the 20 items (ω = .76, 95% CI [.59, .83]) (Dunn et al., 2014).

Knowledge Hypothesis

In support of the knowledge hypothesis, across the conditions, there was a significant moderate negative relationship between structural knowledge scores and control performance in cycle 1 (r = -.34, $p <$ .01).

Table 1. Descriptive statistics, distributions and inter-correlations (Pearson) between the variables for each condition.

		M (SD)	Min.	Max.	Kurtosis (SE)	Skewness (SE)	2	3	4
No Information Condition	1. Structural Knowledge	.21 (.33)	-.49	.98	-.40 (.70)	.38 (.36)	-.38*	-.51**	.45**
N = 44	2. Cycle 1	13.88 (4.20)	4.52	20.77	-.54 (.70)	-.58 (.36)	...	.56**	-.24
	3. Cycle 2	13.21 (5.28)	2.50	25.01	-.58 (.70)	-.31 (.36)	...	...	-.18
	4. APM	63.75 (16.32)	30	95	-.23 (.70)	-.07 (.36)	...	...	...
Information Condition	1. Structural Knowledge	.22 (.35)	-.33	.98	-.47 (.69)	.29 (.35)	-.31*	-.36*	.26
N = 45	2. Cycle 1	13.92 (4.14)	2.82	24.09	.75 (.69)	-.49 (.35)	...	.27	-.11
	3. Cycle 2	10.24 (5.29)	2.10	22.33	-1.03 (.70)	.35 (.35)	...	...	-.52**
	4. APM	58.00 (17.75)	30	95	-.85 (.69)	.06 (.35)	...	...	...

Note. * $p < .05$. ** $p < .01$.

This indicates that participants who acquired more knowledge about the underlying structure of the task produced smaller deviations from the set of optimal control interventions, and were therefore better at controlling the system (i.e., reaching and maintain the goal values). This advantage persisted in cycle 2 even when participants received additional instructions with regard to the underlying structure of the system ($r_{\text{information}}$ = -.36, $p < .01$, $r_{\text{no information}}$ = -.51, $p < .01$).

Information and Intelligence Hypotheses

In order to determine whether the provision of structural information facilitates control performance (Information Hypothesis) and whether the extraction of knowledge from information in this context is determined by fluid intelligence (Intelligence Hypothesis) we conducted a series of two-level HLM analyses. Firstly, a random coefficient regression analysis was conducted to assess whether control performance changed across the two control cycles. At level 1, each participant's performance was represented by an intercept term, which denoted their mean performance across control cycle 1 and control cycle 2, and a slope, that represented their change in performance from control cycle 1 to 2. Control cycle (1 or 2, effect coded as -.5 and .5, respectively) was entered as an independent variable at this level. The mean control performance scores and the change in control performance then became the outcome variables in a level-2 model, in which they were modelled as random effects. The results of this analysis are presented in the top section of Table 2. This analysis indicated that the mean control performance score was 12.81 across control cycle 1 and 2 and on average, control performance scores improved by 2.19 points from control cycle 1 to 2. The change in control performance was significantly different from zero; $t(88)$ = -3.86, $p < .001$. There was significant differences between problem solvers in terms of their mean control performance scores and the change in their control performance; χ^2 = 2867895259.6, df = 88, $p < .001$ and χ^2 = 1274245149.4, df= 88, $p < .001$, respectively. Variability in problem solvers' change in control performance from control cycle 1 to 2 accounted for 64% of the total variability in control performance scores. These findings are an important prerequisite for the subsequent analyses, as they indicate that individuals show substantial variability in their mean control performance and the extent to which their control performance changed across the two cycles.

We conducted an intercept- and slope-as-outcomes regression analysis in which mean control performance and the change in control performance from control cycle 1 to 2 were modelled as a function of condition (as an effect coded variable indicating condition: -.5 = no information, .5 = information) and scores on the APM at level 2. The level 1 model was the same as in the random coefficients regression analysis. The results of this analysis are presented in the middle panel of Table 2.

With regard to the Information Hypothesis, this analysis indicated that information had a significant impact on average control performance scores, and the change in control performance from control cycle 1 to 2, controlling for the effects of fluid intelligence; $t(86)$ = -2.32, $p < .05$, ΔR^2 = 5% and $t(86)$ = -3.19, $p < .01$, ΔR^2 = 9%, respectively. Participants in the information condition had an average control performance score 1.91 points better than those in the no information condition. Similarly, the change in control performance for participants in the information condition was 3.42 points better than those in the no information condition. In support of the Information Hypothesis, these results indicate that participants who received additional information with regard to the underlying structure of the system performed better on average, and improved at a greater rate from control cycle 1 to control cycle 2 than those who did not receive information.

With regard to the Intelligence Hypothesis, the analysis also indicated that APM scores were significantly linked to control performance scores as well as to their change from control cycle 1 to 2, controlling for the effects of condition; $t(86)$ = -3.21, $p < .01$, $\Delta R^2 = 7\%$ and $t(86)$ = -2.17, $p < .05$, $\Delta R^2 = 2\%$, respectively. On average, a one-point increase in scores on the APM was associated with a 0.08 better score on average control performance, and a 0.07 better score on the change in performance scores from control cycle 1 to 2. These results indicate that on average, participants with a higher APM scores, tended to perform better overall, and improved more from control cycle 1 to 2.

In order to determine whether the effect of fluid intelligence on control performance differed by condition a third analysis was conducted in which an interaction term (APM x Condition) was added to the main effects of the variables at level 2. The results are presented in the bottom panel of Table 2. There was no evidence that fluid intelligence (as measured via APM scores) has an effect on mean control performance scores varied by condition, as the interaction term was small and insignificant; $t(85)$ = -.68, p = .50, $\Delta R^2 = 0\%$. However, the effect of fluid intelligence on the change in performance from control cycle 1 to control cycle 2 did vary significantly by condition; $t(85)$ = -2.48, $p < .05$, $\Delta R^2 = 3\%$. In further support of the Intelligence Hypothesis, this suggests that the change in performance scores for participants who received information was more strongly related to fluid intelligence than for participants who did not receive information.

Discussion

This study examined whether: (1) providing guidance in the form of structural information results in an immediate improvement in controlling a CPS task after knowledge has already been acquired through an unguided exploration of the system variables; and (2) any improvements are moderated by fluid intelligence as measured via APM. In summary, support was found for the Knowledge Hypothesis, as participants who acquired more structural knowledge during the exploration phase had better control performance in control cycle 1. Support was also found for the Information Hypothesis, as participants who received structural information improved their control performance more than those who received no information. Finally, support was found for the Intelligence Hypothesis, as when participants received information, their change in control performance scores from control cycle 1 to 2 was more strongly related to APM performance scores than the change in control performance scores in participants who did not receive structural information. These results suggest that guidance in the form of structural information does confer an additional advantage in controlling a complex system over independently acquired knowledge, and that problem solvers can translate such information into effective control actions without practice. However, the extent to which problem solvers can benefit from such information appears to be moderated by their fluid intelligence as measured via APM.

As in previous studies, it was found that the amount of structural knowledge acquired by participants is strongly related to the quality of their control performance. In addition, in line with other studies, few participants were able to acquire complete knowledge of the underlying structure of the system during the exploration phase (Beckmann, 1994; Beckmann & Guthke, 1995; Burns & Vollmeyer, 2002; Funke & Müller, 1988; Müller, 1993; Kröner, 2001; Kröner et al., 2005; Kluge, 2008; Osman, 2008; Schoppek, 2002; Vollmeyer et al., 1996). These findings provide further evidence that learners require additional support or guidance to acquire complete and accurate knowledge about complex and dynamic systems; they are unlikely to do so through unguided discovery learning.

This study also found that guidance in form of providing structural information resulted in an immediate improvement in control performance. In contrast to previous studies (Preußler, 1998; Putz-Osterloh, 1993; Süß, 1996), these findings suggest that a period of active practice is not required to translate knowledge into effective control actions. One caveat to this conclusion is, however, that the task used in other studies could be considered more complex than the task used in the current study. Further studies are required to determine whether the findings observed in this study generalise to more complex tasks.

Nevertheless, the results support and extend upon the findings of Goode and Beckmann (2010) in important ways. As in Goode and Beckmann's (2010) study, the results of the present study show that if problem solvers receive a direct demonstration as to how each input affects each output, and have access to this information in form of a causal diagram during control performance, then they will be able to immediately translate this information into the appropriate actions for controlling the system. This provides further support for the claim that supporting information should be available throughout the task (Berry & Broadbent, 1987; Gardner & Berry, 1995; Leutner, 1993).

Indeed, comparing the findings from the current study with Goode and Beckmann's (2010) study, which employed the same CPS task, instructional method and participants drawn from the same university student population, suggests that an unguided, albeit "active" exploration of the system variables provides no advantage for control performance whatsoever. In Goode and Beckmann's (2010) study, participants received structural information and then were required to immediately control the system variables; mean control performance scores were 10.33 (SD = 5.25) in the comparable control cycle. In the current study, mean control performance scores were 10.24 (SD = 5.29). This suggests that the actively acquired knowledge and practice controlling the system variables resulted in no net advantage for control performance over simply providing structural informa-

Table 2. Results of the Random Coefficients Regression (RCR) Analysis and the Intercept- and Slope-As-Outcome Regression (ISAOR) Analyses

Variable	Parameter Estimate	SE	t	ΔR^2
RCR Analysis				
Mean control performance (β_{00})	12.81	0.43	30.10**	
Mean change in control performance (β_{10})	-2.19	0.57	-3.86**	
ISAOR Analysis 1				
Intercept-as-outcome				
Condition (β_{01})	-1.91	0.82	-2.32*	5%
APM (β_{02})	-0.08	0.02	-3.21**	7%
Slope-as-outcome				
Condition (β_{11})	-3.42	1.07	-3.19**	9%
APM (β_{12})	-.07	0.03	-2.17*	2%
ISAOR Analysis 2				
Intercept-as-outcome				
Condition (β_{01})	-1.89	.82	-2.33*	5%
APM (β_{02})	-0.08	.02	-3.32**	7%
Condition x APM (β_{03})	-0.03	.04	-0.68	0%
Slope-as-outcome				
Condition (β_{11})	-3.38	1.03	-3.29**	9%
APM (β_{12})	-0.06	.03	-2.37*	2%
Condition x APM (β_{13})	-0.13	0.05	-2.48*	3%

Note. * $p < .05$. ** $p < .01$.
Level 1 model (for all analyses):
$Y_{ti} = \pi_{0i} + \pi_{li}$(Control Cycle),
where Y_{ti} is person i's control performance score at time t, π_{0i} is their mean control performance score and π_{li} is their change in control performance from control cycle 1 to control cycle 2.
Level 2 model for RCR Analysis:
$\pi_{0i} = \beta_{00} + \mathrm{r}_{0i}$
and
$\pi_{li} = \beta_{10} + \mathrm{r}_{li}$
Level 2 model for ISAOR Analysis 1:
$\pi_{0i} = \beta_{00} + \beta_{01}(\text{Condition}) + \beta_{02}(\text{APM}) + \mathrm{r}_{0i}$
and
$\pi_{li} = \beta_{10} + \beta_{11}(\text{Condition}) + \beta_{12}(\text{APM}) + \mathrm{r}_{li}$
Level 2 model for ISAOR Analysis 2:
$\pi_{0i} = \beta_{00} + \beta_{01}(\text{Condition}) + \beta_{02}(\text{APM}) + \beta_{03}(\text{Condition x APM}) + \mathrm{r}_{0i}$
and
$\pi_{li} = \beta_{10} + \beta_{11}(\text{Condition}) + \beta_{12}(\text{APM}) + \beta_{13}(\text{Condition x APM}) + \mathrm{r}_{li}$
Note: When intercepts are outcomes, ΔR^2 is expressed as a percentage of the variability in mean control performance scores.
When slopes are outcomes, ΔR^2 is expressed as a percentage of the variability in the change in control performance.

tion. The finding that participants in the no information condition showed little improvement across the control cycles further reinforces this claim. This suggests that practice at controlling the system does not have a significant impact upon the quality of problem solvers' control performance, especially if the control goals change.

Indeed, under both conditions the high level of internal consistency in control performance scores further suggests that problem solvers do not dramatically change their control behaviours through practice. Subsequently, improvements in control performance with practice are rather limited. In other words, these results seem to suggest that no spontaneous optimisation of control behaviour (i.e. learning by doing) takes place. The question, however, of whether longer periods of active practice after exposure to guiding information, would lead to further improvements, could be of interest in future studies.

These findings are consistent with recent findings regarding CPS training. Kretzschmar and Süß (2015) trained participants using five different computer-based complex dynamic systems, and their performance was tested in a sixth system. Interacting with each system involved a goal-free exploration phase and a control phase. They found that trained participants were able to acquire more knowledge about the final system than an untrained control group. However, there was no difference in control performance. In line with the findings from our study, this suggests that for each control intervention, the problem solver must apply their knowledge to generate the correct action for that specific situation.

With regard to the relationship between fluid intelligence and control performance, it should first be acknowledged that the generalisability of the results from this study may be limited by the narrow operationalisation of fluid intelligence via APM. Whilst the APM has been traditionally seen as the empirical reference point of fluid intelligence, more recent discussions (e.g., Gignac, 2015) are critical of studies that rely on this single test score. This on-going debate should be kept in mind while reading the following interpretation of the findings.

The results of this study are in line with previous studies that have shown that when structural information is provided, control performance is moderately to strongly correlated with fluid intelligence (Bühner et al., 2008; Goode & Beckmann, 2010; Kröner et al., 2005; Putz-Osterloh, 1981; Putz-Osterloh & Lüer, 1981; Wüstenberg et al., 2012). This suggests that more intellectually capable problem solvers are able to make use of structural information more effectively than individuals who are less so. This study extends on these previous findings, as it was also found that fluid intelligence as measured via APM had an impact on the acquisition of structural knowledge during the exploration phase, and subsequently in controlling the system when only incomplete knowledge was available. These results suggest that intellectually more capable problem solvers are at a double advantage in comparison to those who score lower on fluid intelligence with regard to acquiring and utilising structural knowledge: they are able to acquire more knowledge without assistance, and they also benefit more from guidance. This implies a necessity to tailor instructions to problem solvers' intellectual capacity, an aspect often neglected in educational contexts. In other words, and as frequently advanced by Snow (1986; 1989; Snow & Lohman, 1989; Snow & Yallow, 1982), individual differences among learners still "...present a pervasive and profound problem to educators" (Snow, 1989, p. 1029).

The results with regard to the role of fluid intelligence also provide support for the claim that in previous studies (Preußler, 1996; Putz-Osterloh & Lüer, 1981; Putz-Osterloh, 1993), the effect of structural information on control performance may have been masked by individual differences in the ability to understand and utilise the information. In addition, Preußler's (1998) finding that all of her participants were able to effectively utilise information after a period of active practice, may now be interpreted in a different light. It may be that practice per se is not the essential component, but rather that some problem solvers require more extensive guidance in order to be able to make sense of the information that is provided.

Overall, our results imply that guidance in the form of structural information has the potential to provide benefits over and above the effects of discovery learning. The crucial aspect of guidance, however, is that it is well designed. These findings are in line with those from other domains that show that learners experience many difficulties when they are required to independently acquire knowledge without guidance (de Jong & van Joolingen, 1998; Mayer, 2004; de Jong, 2005; 2006; Kirschner et al., 2006).

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